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Uncertainty in climate change impacts on water resources

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ABSTRACT

The uncertainty concepts play a prominent role in global environmental change research, including climate change science and climate change impact science, with hydrology and water resources research in particular. One is uncertain, to varying degrees, about virtually everything in the future as well as about much of the past and the present state. The present paper reviews applications of the uncertainty notion to results of change detection, process understanding and modeling of systems, and – foremost – projections of future climate change impacts on water resources. We present a framework of assessing and reducing uncertainty and propose measures that could improve uncertainty communication, e.g. relying on ensembles and multi-model probabilistic approaches rather than projecting ranges of values. We distinguish two possible management strategies if uncertainty is irreducible – the precautionary principle and the adaptive management.

1. Introduction

The common-sense meaning of the term “uncertainty” denotes lack of certainty about something, ranging from small doubts and minor imprecisions to a complete lack of definite knowledge. The broad term “uncertainty” has many various interpretations and may mean different things to different people.

Uncertainty framing raised broad recognition, in relation to the “known knowns” (the things we know we know), “unknown knowns” (unknown but knowable) and “known unknowns” (expected or foreseeable conditions). The most puzzling notion is that of “unknown unknowns”, referring to things we don't know we don't know. They can be virtually unthinkable and may result from unforeseeable conditions that have never occurred, hence cannot be anticipated based on past experience or investigation.

The term “uncertainty” is used in different contexts in natural and social and management sciences. In natural sciences, it is, primarily, an attribute of the research process, going back to the Platonic view of reality that is out there as such, however, human beings can never fully grasp it. Here, uncertainty is related to the inaccurateness of humanly devised models and research tools to describe and represent the reality (Smithson, 1989). In social sciences, the primary focus is on uncertainty impact on human decision-making (e.g. Lipshitz and Strauss, 1997).

Uncertainty can be generally categorized as either epistemic or aleatory (Beven, 2016). The former is a consequence of a lack of knowledge, arising due to human ignorance and indolence. It can be reduced by gathering more data or by refining models. The latter is related to the intrinsic randomness of a phenomenon, hence there is no possibility of reducing it.

In taxonomy of uncertainties proposed by Beven (2016), epistemic uncertainty is subdivided into uncertainty related to system dynamics, forcing and response data, as well as disinformation. In addition, he recognized semantic/linguistic and ontological uncertainties. The former concept refers to uncertainty about the meaning of terms and the latter is associated with different belief systems.

Benestad et al. (2016) reviewed the concept of “agnotology”, being a counterpart to epistemology. It addresses the question “why we don’t know what we don’t know?”. With respect to climate change, ignorance can be a result of absence of knowledge and understanding or of the “inconvenient truth” syndrome (Kundzewicz and Matczak, 2012).

In last decades, uncertainty has played a prominent role in global environmental change research, including climate change science and climate change impact science. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2014) defines uncertainty as a lack of complete information, as well as incomplete knowledge or disagreement on what is known and knowable.

This paper examines the notions of uncertainty in climate change impact assessment on water resources, important in assessing the range of potential outcomes that can be related to observation data, to process understanding and modelling as well as – foremost – to projections for

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the future. Uncertainty assessment and opportunities for its reduction as well as implication for management are also discussed.

2. Process understanding and modelling

The Earth climate system, the principal natural driver of water resources, is very complex. There are external climate drivers, such as the solar radiation, the Earth's orbit, volcanic eruptions, collisions of celestial bodies with the Planet, properties of the atmosphere (therein atmospheric concentrations of greenhouse gases, GHGs) and land surface. Moreover, there are internal feedbacks in the system, diminishing or amplifying the effects and generating high variability. Climatic oscillations in the Ocean-Atmosphere system (such as El Niño Southern Oscillations, North Atlantic Oscillation, Arctic Oscillation, Atlantic Multidecadal Oscillation, Pacific Decadal Oscillation, etc.) are of importance for water resources. Advanced climate models intend to mimic essential physical mechanisms and internal feedbacks. However, the model-based reconstruction of past climate is still far from being satisfactorily accurate (Trenberth, 2010). Unknowns about climate change dynamics are true unknowns, so that improvement of understanding of climate dynamics as well as feedback loops and interconnections is needed (Kundzewicz and Stakhiv, 2010). Some authors bring attention that uncertainty is an attribute of research on complex systems that are not fully understood and there is a certain degree of unpredictability involved in the interactions of the system components (Funtowicz and Ravetz, 1990). Dynamic systems featuring deterministic chaos are a case in point (Lorenz, 1995).

There is a fine aphorism that all models are wrong but some are useful (Box and Draper, 1987). Indeed, there are uncertainties everywhere in modelling and acknowledging them is important. Uncertainties in the climate impact on water resources result from natural complexity and variability of systems and processes, and from deficiencies in our knowledge and models.

Remarkable uncertainty of climatic input to hydrological models comes on top of the "traditional" uncertainty existing in hydrological models that can be related to portraying relations between variables, choice of model structure and parameterization as well as to parameter estimation. Much work has been done on hydrological uncertainty, see review by Nearing et al. (2016). Uncertainty can be involved in the input data (due to data scarcity, measurement errors, lack of representativeness of the measurement site, or problems in aggregating or disaggregating data in order to cover areas of concern). Uncertainty can be inherent in the variables and their distributions, but also in uncertain model error resulting from selection of the form of the probabilistic submodels, the probability distribution, and the physical models, including empirical equations. Uncertain errors are involved in measurements and observations, based on which the parameters are estimated, including errors involved in indirect observation, e.g., the determination of a quantity through a proxy.

It can be expected that, after successful calibration, the degree of uncertainty in a parameter estimate in a hydrological model would be lower than the uncertainty associated with the prior estimate before calibration, and uncertainty of outputs related to hydrological model would be reduced (Krysanova et al., 2017a,b). Reduction of uncertainty is a measure of relevance of a parameter. Uncertainty of parameter estimation is possibly inversely related to the information encapsulated in field observations.

3. Projections for the future

There are many sources of uncertainty in model-based projections for the future. For instance, there is uncertainty in knowledge of the external environment, uncertainty regarding future intentions driving choices, as well as uncertainty regarding the value judgments of consequences.

Technically speaking, uncertainty in projections of climate change impact on water resources is due to: (i) scenarios of future socio-economic development, (ii) GHG emission and sequestration scenarios, (iii) General Circulation Models, GCMs, (iv) Regional Climate Models, RCMs, or statistical downscaling methods, (v) choice of the bias correction method (if applied), (vi) input data for hydrological model(s), (vi) hydrological model(s) structure(s), and (viii) parameterization of hydrological model(s).

One can observe a forward-propagation (and likely increase) of uncertainty through a multi-stage process of developing projections of climate change impact on water resources and adaptation of the water sector to climate change. On the other hand, adding new information to the process (bringing in local observations, empirical knowledge, physics-based dependencies, statistical theory, etc.) constrains the range of possible outcomes. Every transfer function or modelling step bears uncertainty, as well as it may entail new information (i.e. Wilby and Dessai, 2010).

Uncertainties are introduced by the transfer functions: from GHG emissions and sequestration to atmospheric GHG concentration, further to climate change (global to regional to local), and then to impacts on water resources (and particularly on extreme hydrological events), as well as adaptation (Kundzewicz et al., 2017).

The uncertainty starts from the unknowns about the future society, as future development of socio-economic driving factors (population number, economic development/wealth and life style patterns, technology) is largely unknowable, and cannot be assigned objective probabilities. For this reason, it is suggested that a range of scenarios be applied in impact assessments rather than a single best-guess or average case. Differences in trajectories of atmospheric GHG concentrations (resulting from emission and sequestration) are a clear and important reason of discrepancy in water-related projections. There are two broadly applied approaches: one based on the IPCC Special Report on Emission Scenarios – SRES (Nakicenovic and Swart, 2000) and a more recent one, based on the concept of Representative Concentration Pathways (RCPs) (cf. Meinshausen, 2011). Some experts (Katz, 2002) propose that because all scenarios are not equally likely, one could try to envisage weighting each scenario by its likelihood.

There can be a large difference between results obtained by using different scenarios and different climate models, especially on local and regional scales. Intra-model uncertainty of projections (for the same model and different scenarios) can be lower than the inter-model uncertainty (for the same scenario and different models). Uncertainties in climate change projections clearly depend on the future time horizon of concern, usually increasing for a more remote horizon. In the near future (e.g. 2020s), climate model uncertainties may play a more important role than GHG emissions, because near-term climate is strongly conditioned by past emissions (committed warming), while for far future (e.g. 2090s), uncertainties due to the selection of future emission (and sequestration) scenarios may be more important. Sometimes, the picture is more complex (cf. Vetter et al., 2017).

Also differences in GCMs, RCMs and downscaling techniques are crucial. In older studies, only one GCM output was used, whereas ensembles of several climate models have been consequently used in recent studies. The selection of GCMs, as well as of a downscaling technique (empirical-statistical or dynamic) can explain a major portion of differences in reported projections (Vetter et al., 2017). Climate models do not satisfactorily simulate the present-day climate, showing large biases. Hence, a statistical bias correction is often carried out in order to render the model output closer to observation data in the reference period. The observations also are subject to errors, depending on the variable, location, and observational practices and changes over time (e.g. new instruments, relocation of instruments, or changes in the surroundings).

In high latitudes and parts of the tropics, climate models are consistent in projecting future precipitation increase, while in some subtropical and lower mid-latitude regions, they are consistent in projecting precipitation decrease and river flow may grossly follow the

precipitation change (Kundzewicz et al., 2008; Doell et al., 2015). Between these regions, there are areas where climate models of the current generation do not agree even on the sign of future precipitation change. This means that projections of precipitation – the principal meteorological input signal to hydrological systems – resulting from various climate models and from various assumptions about the future socio-economic developments, driving the GHG concentration pathway, can be largely different. Clearly, climate models are not "ready for prime time" (Kundzewicz and Stakhiv, 2010), i.e. cannot be directly used in the realm of many real-world applications in the water management sector and infrastructure planning and design.

Uncertainty in water-related projections is also due to a spatial and temporal scale mismatch between coarse-resolution climate models and the small-scale of hydrological models for a river basin, for which a much finer information is necessary. Hence, disaggregation of information from climate models is usually needed. River basins may range from the micro-scale (far below a single climate-model grid-cell) to the continental scale for very large rivers (covering many climate-model grid-cells).

It turns out that different hydrological models, driven by the same climate input, can yield surprisingly contrasting projections. The global hydrological models (GHMs) can provide meaningful simulations across very large scales and can be useful for getting global or continental overviews, but they have to compromise the model performance in the meso- to macroscale river basins, and feature much higher uncertainty ranges compared with the basin-scale models (Hattermann et al., 2017). For instance, the GHMs are mostly used without any calibration and validation at the basin scale, while it is a must for the basin-scale models. This is likely to be an important reason for differences in projections and uncertainty ranges in simulations by the global and basin-scale models for large-scale studies (Hattermann et al., 2017; Krysanova et al., 2017a,b).

Some authors argue for using only the best performing hydrological models, selected based on their ability to reproduce observed variables of particular interest for the problem at hand and the area of concern. As noted by Carter and Hulme (2000), models should be excluded from consideration in impact assessments if their performance against past observations is inadequate or their range of operation is limited to present-day conditions. Model 'invalidation' may thus be a relevant goal of model testing and could serve to narrow the uncertainty range of impacts by excluding poorly-performing models. Nevertheless, some experts advocate the necessity of using ensembles of all available hydrological models, rather than removing the models that do not perform sufficiently well in the calibration and verification stages. Indeed, the jury is still out on what is the optimal process (Krysanova et al., 2017a,b).

On the top of uncertainty related to future water availability, there is a considerable uncertainty about future water demand. Indeed, water recycling and more efficient technologies can decrease the overall water demand. Irrigation of bioenergy crops and cooling technologies for electricity generation are among the most influential factors affecting future water demand in the context of climate change mitigation (Mouratiadou et al., 2016).

4. Uncertainty language and uncertainty assessment

In general, measurement of uncertainty is based on identification of a set of possible states or outcomes for which probabilities (objective or subjective) are assigned (including a probability density function for continuous variables). Mastrandrea et al. (2010) proposed two metrics for representing the degree of uncertainty in key findings in the domains of the Intergovernmental Panel on Climate Change (IPCC): confidence in the validity of a finding and quantified measures of uncertainty in a finding. The latter is expressed probabilistically (in an objective way – based on statistical analysis of observations or model results, or a subjective way – reflecting the expert judgment or Bayesian statistics).

This was the backbone of the calibrated uncertainty language in the Fifth Assessment Report of the IPCC Working Group II (Field et al., 2014). A level of confidence (illustrating evidence and agreement) was expressed using five qualifiers: from *very low* to *very high.* The assessed likelihoods of outcomes ranged from *virtually certain* (99–100% probability) to *exceptionally unlikely* (0–1%). An example of application of the calibrated uncertainty language from the water-resources chapter by Jiménez Cisneros et al. (2014) follows: "Climate change is *likely* to increase the frequency of meteorological droughts (less rainfall) and agricultural droughts (less soil moisture) in presently dry regions by the end of the 21st century under the RCP8.5 scenario (*medium confidence*). … This is *likely* to increase the frequency of short hydrological droughts (less surface water and groundwater) in these regions (*medium evidence, medium agreement*)."

Nearing et al. (2016) proposed the organizing principle behind uncertainty quantification: "How much information do we have and how well do we use it?". Assessment of uncertainty allows to generate more robust results by quantifying the agreement between climate models in impact projections. In the Fourth IPCC Assessment Report (Solomon et al., 2007), simple counting of the number of models that show agreement in the direction of a change was suggested as a useful measure. In general, intercomparison of impacts projected by applying sets of climate model scenarios and sets of impact models allows to quantify agreement between model outputs, by explicitly taking into account the agreement in projections and statistical significance of change. A combination of these two properties was labelled as robustness by Knutti and Sedlácek (2013).

Traditionally, the range of projections (spread of model outcomes) is used as a proxy measure of uncertainty and the mean or median (the latter being more outlier-robust) of the ensemble of model projections is often advocated as a useful representation of the future. It is assumed that the greater the number of models in agreement, the stronger the robustness, but this stance has shortcomings. The ultimate quality index is the difference between model outputs and reality (often unknown or even unknowable). What if most (or all) models turn out to be wrong in projecting a change in a variable of interest?

Katz (2002) reviewed methodology for quantifying uncertainty, including sensitivity and scenario analyses, as well as a formal probabilistic approach. Sensitivity analysis is based on computing a partial derivative of model response with respect to input or a what/if analysis (e.g. under assumption of a 1 °C warming or 10% increase in precipitation). Scenario analysis uses a set of scenarios for model inputs to be transformed into model outputs. In Monte Carlo analysis, the inputs are randomly drawn from probability distributions and the corresponding outputs are determined, producing a probability distribution for the output.

The variance decomposition method (ANOVA) is a tool for decomposition of the total ensemble uncertainty into contributions from different sources and interactions between them (cf. von Storch and Zwiers, 1999). The relevant equations can be found in Bosshard et al. (2013), who showed that different sample sizes of the uncertainty sources can result in a biased variance decomposition. To avoid such a bias, they proposed a subsampling scheme.

Based on the published results, cf. Vetter et al. (2017) and review in Krysanova et al. (2016), it can be concluded that the GCMs and GHG emission scenarios are usually two major sources of uncertainty in climate change impact assessment on water resources.

The current approach to dealing with climate model and impact model uncertainties is to perform studies where the output of several climate models is used as input to several hydrological models to produce an ensemble of potential changes. Multi-model studies typically assume that each combination of climate model and hydrological model runs are given the same weight (even if some model(s) perform poorly in. a region of interest), or else the impact models are weighted based on their performance in the control period.

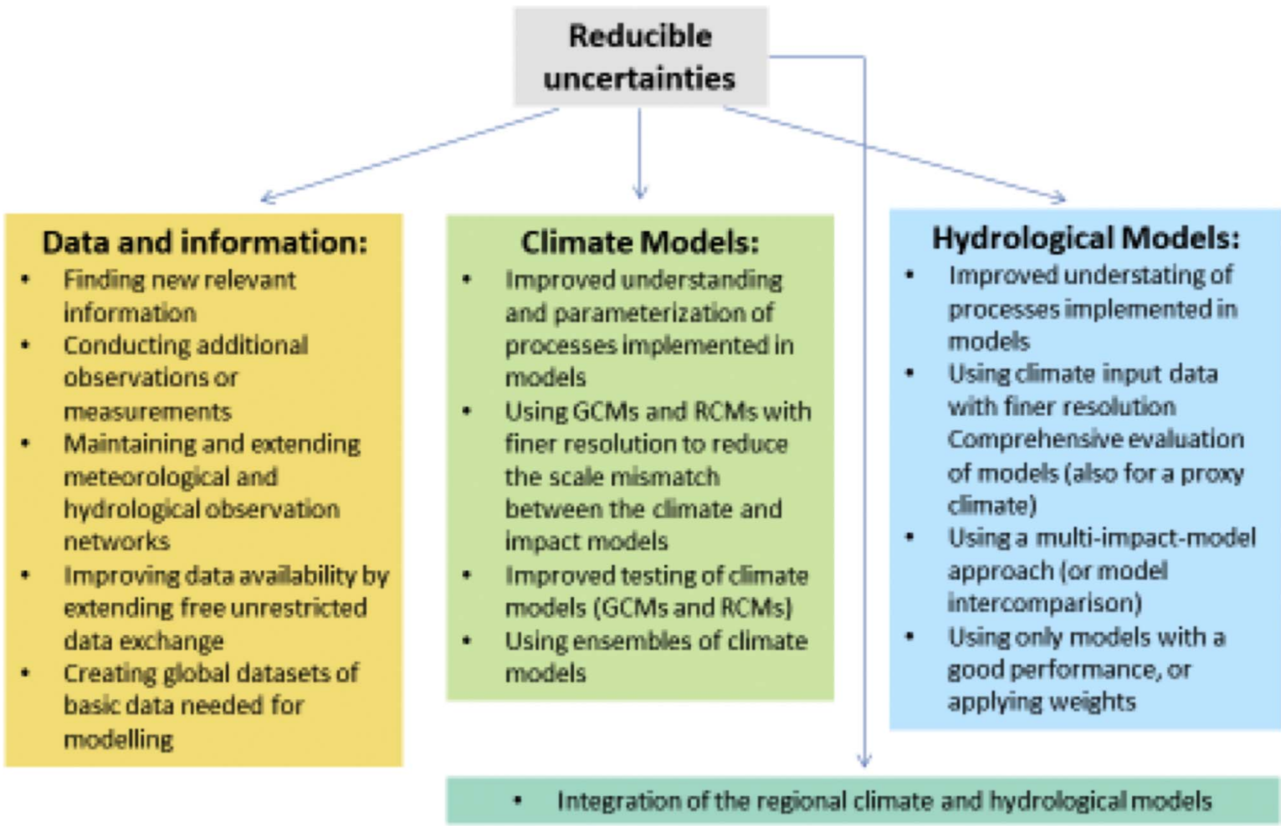

Fig. 1. A general framework for reducing uncertainty in assessment of climate change impact on water resources.

In summary, as put by Beven (2016), estimates of uncertainty are conditioned on the assumptions made.

5. Reducing uncertainty

A general framework for reducing uncertainty in assessment of climate change impact on water resources is presented in Fig. 1. In this chapter, opportunities of uncertainty reduction in data and information, climate models, and hydrological models will be outlined.

5.1. Data and information

Progress of computers, user-friendly operational systems, and application software has made it possible to perform and repeat, within a short time, complex calculations that use large quantities of data and numerous equations. Climate impact assessments are usually being done by multiple model runs. Hence, the computational barrier, that used to hamper progress until quite recently, has been overcome.

Epistemic part of uncertainty (resulting from incomplete or unprecise information) may be reduced by the act of obtaining more exact information (by way of finding a relevant new fact, conducting additional observations or measurements, etc). The amount of useful additional information obtained by such action measures the reduction of uncertainty.

Reducing uncertainty in projections of climate change and its impacts has been among the most burning research needs, in order to reliably inform the stakeholders and to better assist impact communities in their duty to adapt to change.

Critical problems are related to data availability and understanding of processes encapsulated in climate and hydrological models. Removing or weakening of data availability problems (e.g. connected with shrinking ground-truth meteorological and hydrological observation networks and lack of free and unrestricted data exchange) would contribute to uncertainty reduction (e.g. in drawing corollaries about the trends, making attribution statements, as well as modelling and generating projections for the future). The emerging availability of global datasets and remote sensing data enables model intercomparisons, and may lead to uncertainty reduction (e.g. Vetter et al., 2017).

It is worth trying to reduce uncertainty by the use of open standards to share water information, such as the Open Water Data Initiative (Maidment, 2016) or the SWITCH-ON Virtual Water-Science Laboratory (Ceola et al., 2015). Indeed, open data policies are being developed, leading to liberation of data from closed repositories, improved interoperability via online data access standards, and scalable (often cloud-based) mechanisms for massive data storage and computing. Now, users are increasingly expecting data and related applications to be available immediately, easily, openly, and in great quantities (Brodaric and Piasecki, 2016).

Due to shortness and incompleteness of hydrological records, it is necessary to seek complementary data sources, in order to improve knowledge of past and ongoing system dynamics and to further our understanding of future situation, also in a context of climate change. For instance, data on past floods in some regions are scarce and typically censored toward extremes (Stoffel et al., 2016). In many mountain regions, the observations networks are discontinuous and short-operating. Hence, it is necessary to find complementary data sources to improve understanding, e.g. with the help of botanical evidence, such as scars on trees. Ballesteros-Cánovas et al. (2016) presented a paleohydrological reconstruction for floods in mountain streams in the Tatra Mountains in Poland, using scars in trees to assess paleostage levels.

5.2. Climate models

Climate models need to be improved before they can be effectively used for adaptation planning and design. Substantial reduction of the

uncertainty range would require improvement of our understanding of processes implemented in models and using finer resolution of GCMs and RCMs. However, important uncertainties are unlikely to be eliminated or substantially reduced in near future (cf. Buytaert et al., 2010). Uncertainty in estimation of climate sensitivity (change of global mean temperature, corresponding to doubling atmospheric CO_2 concentration) has not decreased considerably over last decades. Higher resolution of climate input for impact models requires downscaling (statistical or dynamic) of GCM outputs, adding further uncertainty.

Trenberth (2010) formulated a catchy slogan: "more knowledge, less certainty" that, in fact, is not paradoxical. Our knowledge grows with time and we find factors that were ignored earlier in climate models. Rather than being unknown unknowns, they tend to be unknown knowns. Hence, the perceived uncertainty can grow because of increased knowledge and more sophisticated approaches, that is, an apparent increase in uncertainty can be anticipated in short term, rather than reduction (Katz, 2002). The early quantitative projections of climate change impact on water resources performed with just one climate model (and one hydrological model) gave naïve illusion of certainty. We had one result, regarded as crisp and solid, because there was no disagreement between different results of several models.

End-to-end attribution of climate change impacts on water resources, from GHG emissions to hydrological variables, is typically not undertaken, because it would require experiments with climate models in which the external natural and anthropogenic forcing is "switched off". Besides, climate models do not currently simulate the water cycle at sufficiently fine resolution for attribution of catchment-scale hydrological impacts to anthropogenic climate change. It is expected that climate models and impact models will become better integrated in the future. However, as for now, it is necessary to rely on multi-step attribution, in which hydrological changes are shown to result from climatic changes that in turn result from human activities. Problems related to a scale mismatch between models (large grid cells in climate models vs much smaller grid cells in hydrological models) have to be solved.

5.3. Hydrological models

Improvement of hydrological models can lead to reduction of uncertainty. Process-based distributed models use small-scale equations often based on a problematic assumption that using "effective" parameter values one can cope with the change of scales. However, better sub-grid scale parameterization is clearly needed, based on large-scale measurements rather than aggregation of a small-scale theory (Krysanova et al., 2016).

Existing models may not be able to solve the increasingly complex, inter-disciplinary problems, including biotic and socio-economic components. Hence, it is often necessary to make use of several models, or to extend the existing models in order to cover additional processes. In the past, this has been achieved by modeling the different processes separately and using the outputs of one model as inputs to the next, but then the feedbacks existing in complex systems were ignored or considered only partly In contrast, one can run the models in parallel, whereby the links between processes are coupled at each time step of the simulation and feedback mechanisms are included.

However, ongoing improvements in the process description of hydrological models may not substantially reduce the overall uncertainty, because incorporation of additional components and/or parameters in the models could increase uncertainty bounds.

Selecting appropriate hydrological models is crucial. Among the technical factors and criteria involved in the selection process are: the general modeling objective; the scale of the study; the representation of most relevant processes, the variable(s) of interest; the climatic and physiographical characteristics of the catchment; data availability *vs* data requirements for model calibration and validation; model complexity level and ease of application. Model selection depends also on previous models applications in the region of interest and experience of the modelers. It can be seen as an optimization task, where a modeling task is defined (requiring an appropriate model performance), along with quality criteria or indicators (measuring how well the model performs), and constraints (e.g. on available data, human and financial resources, and time requirements). However, proliferation of models and scarcity of (much needed) studies where ensembles of impact models are applied (cf. Krysanova and Hattermann, 2017) render selection of an optimal model, for a given application, difficult.

When selecting hydrological models and using them, it is always essential to be aware of the limitations of model applicability, assumptions made, as well as simplifications, omissions and mis-specification in model development. Further, it is important to examine in advance whether a model in question has been thoroughly tested in a variety of environments, including conditions similar to these of the study at hand.

Calibration and validation of a hydrological model should be done before applying it for climate change impact assessment, to reduce the uncertainty of results. Yet, typically, global hydrological models are not calibrated and validated. The calibration could start from a parameter sensitivity analysis followed by manual and/or automatic identification of values of model parameters. A good calibration and validation practice includes testing the model performance for all relevant variables in a spatially-distributed mode (Krysanova et al., 2016), rather than in one point (catchment outlet) only. Another noteworthy practice is looking beyond the river discharge in calibration, by including remote sensing and/or in-situ data. This may help reduce uncertainty range of model parameters and equifinality (Rajib et al., 2016).

Until recently, in most studies reported in literature, a single hydrological model was used to assess climate change impacts on water resources. The model was typically driven by downscaled (statistically or dynamically) and bias-corrected output from a number of climate models – GCMs or RCMs, fed with GHG emission scenarios. Another option was to use the delta-change method. Some papers use RCM outputs directly, without any bias correction. Use of multiple hydrological models for impact assessment is becoming a more common approach now (Krysanova and Hattermann, 2017).

Checking hydrological model performance in the historical period is needed, using a comprehensive approach like differential split sampling involving proxy climate conditions as projected for future, and excluding the models with poor performance from impact assessment or weighting their results based on performance. The calibration and validation procedure (also called evaluation) should include several goodness-of-fit criteria covering different aspects. The most commonly used criteria include Nash and Sutcliffe efficiency, percent bias, residual variation, and coefficient of determination (Krysanova et al., 2016), as well as Kling-Gupta efficiency (Gupta et al., 2009).

Model intercomparison for the water sector was carried out in the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) with global-scale and regional-scale hydrological models. This embraces projections, obtained with global models, of mean annual discharge and water scarcity (Schewe et al., 2014), magnitude and frequency of floods (Dankers et al., 2014), hydrological drought severity (Prudhomme et al., 2014), and combined analysis of climate change impact and effects of direct human interventions on water resources (Haddeland et al., 2014). The regional-scale projections for 12 large river basins worldwide (see a synthesis in Krysanova et al., 2017a,b) show trends in mean flow and high and low percentiles: Q_{10} and Q_{90} (Vetter et al., 2017), changes in seasonality of river discharge (Eisner et al., 2017) and extremes (Pechlivanidis et al., 2017; Samaniego et al., 2017), and include uncertainty analysis related to RCPs, GCMs, and hydrological models (Vetter et al., 2017). For the cross-scale comparison of global and regional model performance, simulated impacts and uncertainties, see Hattermann et al. (2017) and Gosling et al. (2011).

6. Implications of uncertainty for management

Model-based projections of climate change impact on water resources can largely differ. If this is the case, water managers cannot have confidence in an individual scenario or projection for the future. Then, no robust, quantitative, information can be delivered and adaptation procedures need to be developed which use identified projection ranges and uncertainty estimates. Moreover, there are important, non-climatic, factors affecting future water resources.

Stakhiv (2010) found the information available from GCMs to be inadequate for water management decision-making. Water managers are not comfortable with a proliferation of climate models, each generating countless scenarios, that they have to contend with. Why should there be burden on the water management community to reconcile the disparate outcomes? – asks Stakhiv (2010).

If uncertainty is irreducible, then two alternative courses of action can be envisaged – the precautionary principle and the adaptive management. The former is a variation of the min-max concept – to choose the approach minimising the worst outcome, of vast importance if there are threats of serious or irreversible damage. The latter is backed by observation that, in light of the broad range of results for different climate impact scenarios, adaptive planning should be based on ensembles and multi-model probabilistic approaches. Some adaptation options can perform well under any alternative futures, while others can perform extremely well under some futures, but not other. Some adaptation measures can be no-regret (e.g., doing things that make sense anyway, seeking co-benefits and multiple-win situations) to low-regret, but other measures may entail significant costs (c.f. Heltberg et al., 2009)

In the absence of crisp results produced by the science, the concepts of precautionary climate allowances are being envisaged as a "climate proofing" exercise. Water managers in some European countries are already incorporating the potential effects of climate change into policies and specific design rules acknowledging uncertainty. So-far experience shows that legal rules are most open to uncertainty when infrastructure does not yet exist, whereas adaptation of existing infrastructure is a more complicated matter (Goytia et al., 2016). For instance, traditional design values of precipitation or river flow are increased by a safety margin, reflecting projections, in order to be on the safe (or safer) side. 'Climate change adjustment factors' have been introduced, that should be taken into account in new plans for flood risk reduction measures (cf. Kundzewicz et al., 2008, 2017).

Even if decision makers may be more interested in evidence than uncertainty (Beven, 2016), uncertainty information clearly matters for them. Practitioners regard uncertainty information as a relevant element of their work and try to integrate it into planning and decision-making process (Höllermann and Evers, 2017), even if such task is a major challenge. One option is reframing uncertainty into risk. Doell et al. (2015) show how assessment and reduction of climate change risks can be integrated into water management. Lawrence et al. (2013) examined risk-based approach to flood frequency changes, noting that evaluation of a wider range of response options at the exploratory stages of decision-making helps avoid planning responses that are predicated on historical experience and a single 'best-estimate' scenario. However, decision-making tools for charting adaptive pathways to address uncertainty through alternative futures are needed and have to be developed.

There is a lack of clarity as to how to convey uncertainty, e.g. how to inform policy makers in situations of deep uncertainty of projections of climate change impacts. Aven (2013) noted that handling of deep uncertainties (with potential for surprise) in preparing for climate change is a research challenge. Suitable approaches have to be developed, since the standard probability-based tools are not adequate. We need to better understand how decision makers interpret uncertainty and respond to it, in order to improve the communication. Behavioral and decision-making research shows that the perceptions of uncertainty might differ and that people use various strategies to cope with uncertainty including search for additional information and preparing to avoid or confront a potential risk. Nevertheless, under some conditions, uncertainty might be suppressed by denial, ignorance or distorting undesirable information (Lipshitz and Strauss, 1997). People tend to overweight low probabilities (Kahneman and Tversky, 1979) what might also lead to a false sense of security and the belief that an unfortunate outcome cannot happen to oneself (Matlin and Stang, 1978). Empirical evidence shows that this psychological mechanism can lead to maladaptation or lack of adaptation to environmental hazards. To give an example, large flood control projects provide a false sense of security among riparians and underestimation of a flood probability (Griggs and Paris, 1982). As noted by Funtowicz and Ravetz (1990), in the past, science was assumed to provide "hard" results in quantitative form, in contrast to "soft" determinants of politics, that were interest-driven and value-laden. Yet, the traditional assumption of the certainty of scientific information is now recognized as unrealistic and counter-productive. Policy-makers have to make "hard" decisions, choosing between conflicting options (with commitments and stakes being the primary focus), using "soft" scientific information that is bound with considerable uncertainty. Uncertainty has been policitized in that policy-makers have their own agendas that can include the manipulation of uncertainty. Parties in a policy debate may invoke uncertainty in their arguments selectively, for their own advantage.

Carter and Hulme (2000) examined stakeholders' needs regarding information on uncertainty, noting that there are many different categories of stakeholders, with different requirements for information on climate change and its impacts. Nevertheless, emphasis should be on the robust aspects of assessments (including levels of confidence). Uncertainties should be communicated but an excessive emphasis on uncertainties might detract from important messages about likely consequences of climate change. No doubt, uncertainty information is likely to be most useful if posed in an operational or decision-making context. Often, the goal of stakeholders is to minimise risks. In order to communicate uncertainty by the scientists to stakeholders, the involvement of the latter can be regarded as critical. Dialogue is important to ensure that any evaluation of uncertainties undertaken by scientists is both relevant and expressed in appropriate terms for the stakeholder.

It is common that laymen either inflate uncertainty (i.e. view the scientific results more uncertain than they really are) or downplay uncertainty (i.e. view the science more certain than it really is). Downplaying uncertainty may occur by simplifying scientists' carefully chosen wording, e.g. delivering a definitive, crisp number, rather than a range of possible and plausible futures. Often, there are long figure captions in the IPCC reports, conveying complex and rigorous information, that are distilled to a few words, e.g. in a popular journal article and then the important caveats are lost. Also, stories with a single source or without any context of previous research could mean that the knowledge looks more established and more definitive than it really is.

Refsgaard et al. (2013) proposed a generic framework to characterize climate change adaptation uncertainty with focus on the nature of uncertainty (whether reducible or non-reducible), the level of uncertainty (whether it can be described statistically, as scenarios, qualitatively or is due to ignorance) and the source (origin) of uncertainty. They found that the dominating sources of uncertainty may considerably differ among issues; with most uncertainties on impacts being epistemic (hence reducible) by nature. Uncertainties on adaptation measures are complex, with ambiguity often being added on top of the impact uncertainties.

7. Concluding remarks

Present comprehension of climate change and its past, present, and future impacts on water resources generally suffers from strong

uncertainties because of the gaps in knowledge and insufficient understanding of the complex processes and their feedbacks and interconnections (cf. Funtowicz and Ravetz,1990).

Even if the stock of knowledge increases with time, we find factors that were ignored earlier, hence the uncertainty may also grow. It also seems to grow if we use multi-model ensembles that lead to different simulations, instead of single models.

Remarkable uncertainty of climatic input comes on top of the "traditional" uncertainty existing in hydrology, related to portraying links between variables, choice of model structure, parameterization and parameter estimation. We reviewed metrics for representing the degree of uncertainty and demonstrated how uncertainty can be reduced.

There are many sources of uncertainty in projections for the future, discussed in this paper. Using ensembles of climatic and hydrological models may allow to find more robust results, supported by several models, for some river basins or regions. But, at the same time it can result in large spread of simulations in other regions, and even different directions of change that are difficult to interpret using current tools.

There exists an opinion that decision making should be postponed until sufficient knowledge becomes available (wait-and-see stance). However, as noted by Refsgaard et al. (2013), in some contexts even large uncertainties may imply small consequences for decision making – there can be sufficient knowledge to justify action in climate adaptation.

Since model-based projections of climate impact on water resources can largely differ, adaptation procedures need to be developed which do not need crisp, quantitative, projections of changes in hydrological variables, such as river flow, lake level, soil moisture, etc., but rather on projected ranges of values. Adaptive planning should be based on ensembles and multi-model probabilistic approaches rather than on an individual scenario and a single-value projection for the future. In the absence of robust results produced by the science, the concepts of precautionary allowances are being envisaged as part of "climate proofing" exercises.

The authors hope that this paper contributes to improving interpretation of the notion of uncertainty in climate change impacts on water resources and sketches a roster of challenges in the problem area.

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